

A probabilistic framework for assessing vulnerability to climate variability and change: the case of the US water supply system

Romano Foti · Jorge A. Ramirez · Thomas C. Brown

Received: 7 June 2013 / Accepted: 9 March 2014 / Published online: 15 April 2014
© Springer Science+Business Media Dordrecht 2014

Abstract We introduce a probabilistic framework for vulnerability analysis and use it to quantify current and future vulnerability of the US water supply system. We also determine the contributions of hydro-climatic and socio-economic drivers to the changes in projected vulnerability. For all scenarios and global climate models examined, the US Southwest including California and the southern Great Plains was consistently found to be the most vulnerable. For most of the US, the largest contributions to changes in vulnerability come from changes in supply. However, for some areas of the West changes in vulnerability are caused mainly by changes in demand. These changes in supply and demand result mainly from changes in evapotranspiration rather than from changes in precipitation. Importantly, changes in vulnerability from projected changes in the standard deviations of precipitation and evapotranspiration are of about the same magnitude or larger than those from changes in the corresponding means over most of the US, except in large areas of the Great Plains, in central California and southern and central Texas.

1 Introduction

As our climate changes and human populations continue to expand, an understanding of the vulnerability of the systems on which we rely becomes increasingly important. That vulnerability depends both on a system's ability to withstand stresses and on the magnitude of those stresses. Most importantly, it depends on the inherent probabilistic nature of the bio-physical and socio-economic drivers affecting both the system's capacity and stresses. We introduce a probabilistic

Electronic supplementary material The online version of this article (doi:10.1007/s10584-014-1111-6) contains supplementary material, which is available to authorized users.

R. Foti · J. A. Ramirez (✉) · T. C. Brown

Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, CO, USA
e-mail: Jorge.Ramirez@ColoState.edu

T. C. Brown

Rocky Mountain Research Station, U. S. Forest Service, Fort Collins, CO, USA

Present Address:

R. Foti

Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ, USA

framework for vulnerability analysis and use it to quantify current and future vulnerability of the highly interconnected water supply system of the contiguous United States. We determine the projected changes in vulnerability as well as the relative contributions to those changes from changes in the means and variances of the hydro-climatic and socio-economic drivers. However, modeling the ability to respond to stresses –via, for example, construction of new reservoirs or alteration of allocation priorities– is beyond our goals in this paper. Rather, we seek to determine where such adaptation measures will be needed and, because mitigation and adaptation decisions must account for the inherent variability of the drivers of vulnerability and for the uncertainty in our estimates of their future variability, we determine the range of changes in vulnerability projected by three climate models under two IPCC emission scenarios.

Our analysis is carried out on an annual basis, and thus sub-annual variations in the drivers of vulnerability (i.e., demand and supply) are not taken into account explicitly. Although most of our findings are in general agreement with other such large-scale assessments (e.g., Hurd et al. 1999; Roy et al. 2012; Vörösmarty et al. 2000), our work crucially adds an accounting for reservoir storage, trans-basin diversions and a more comprehensive effort to project water supply and demand. Most importantly, methodologically, it introduces a new probabilistic approach to vulnerability analysis capable of accounting for the inherent variability of the climatic and hydro-economic drivers of vulnerability.

2 Vulnerability

The vulnerability of a system is a function of its ability to respond to inherently variable stressors. Because the magnitude of the stresses and the capacity to withstand them are uncertain, vulnerability should be quantified probabilistically and depends on the joint probability distribution function of capacity and stresses.

For a water supply system, this probabilistic character implies that vulnerability depends on the mean, variance, and co-variance of water supply and water demand. More importantly, it implies that to address questions about future changes in vulnerability, it is not sufficient to quantify the effects of changes in the mean values of hydro-climatic and socio-economic variables of interest – it is necessary also to quantify the effects of changes in the intrinsic variability (i.e., changes in the variance and co-variance) of those variables (see [Supplemental Material](#)).

We quantify the vulnerability, V , of a water supply system as the probability that water demand, D , will exceed water supply, S . Equivalently, defining water surplus, Z , as $S-D$, vulnerability is the probability that Z is negative (Kochendorfer and Ramirez 1996) (see [Supplemental Material](#)). For a given variance of surplus, vulnerability increases as the mean surplus, μ_z , decreases; and for a given mean surplus, vulnerability increases as surplus variance, σ_z^2 , increases if the mean surplus is positive, or it decreases otherwise (see [Appendix A](#)). The dependence of vulnerability on the first two moments of the probability distribution of surplus may also be captured in terms of a reliability ratio, the ratio of the mean surplus to the corresponding standard deviation, $\beta = \mu_z/\sigma_z$ (see [Eq. A.3](#)). The reliability ratio quantifies in units of the standard deviation how far from the critical threshold of zero the surplus of a given location is, with locations of smaller reliability ratios being more vulnerable.

3 Water supply and demand

Both water supply and water demand depend on climate (e.g., precipitation and potential evapotranspiration) and socio-economic drivers (e.g., population, irrigated area). Our approach

to estimating water supply and demand begins with analysis of historical records and with preparation of two alternative scenarios of socioeconomic changes and greenhouse gas emissions corresponding to the IPCC's SRES A1B and A2 scenarios (Nakicenovic et al. 2000; Zarnoch et al. 2010). Future hydro-climatic variables for each scenario were obtained from downscaled projections of three global climate models, CGCM, CSIRO, and MIROC (Price et al. 2006). Annual water supply of a basin was estimated as water yield (the difference between precipitation, P , and actual evapotranspiration from soil moisture, E) plus inflows from upstream basins or trans-basin diversions, plus reservoir storage from the prior year minus evaporation from storage. Water yield was estimated for 5×5 km cells with a detailed physically based, statistical-dynamical hydrologic model (Eagleson 1978) (see [Supplemental Material](#)) driven by hydro-climatic variables. The model was calibrated using historical streamflow records of over 2,000 basins making up the conterminous US. For all basins, the calibrated model matches the average historical streamflows within a 1 % tolerance, and an average relative root mean squared error on the annual water balance across all basins smaller than 18 % (Foti 2011; Foti et al. 2012). The water yield of a basin was computed as the sum of the yields from each interior 5×5 km cell. Our analysis focused on renewable supplies. Thus, mining of groundwater was not included as a source of supply. However, in Section 8 we examine the effect of groundwater mining on current and projected vulnerability in selected basins where data are available.

Annual water demand was estimated as the net amount of water depletion that would occur if water supply were no more limiting than it has been in the recent past, with water depletion (withdrawal minus return flow) projected for each of six categories of water use as a product of a water use driver (e.g., population, irrigated area) and a water use efficiency factor (e.g., domestic withdrawals per capita, irrigation water depth) while taking into account expected trends in water use efficiency as affected by climate change (Brown et al. 2013). Of the six water use sectors—domestic and public, agricultural irrigation, thermoelectric, industrial and commercial, livestock, and aquaculture—projections of the first three were modeled as affected by future changes in precipitation and potential evapotranspiration (Brown et al. 2013).

We estimate the vulnerability of the water supply system over the 21st century for 98 basins, called Assessment Sub-Regions (ASRs) (U.S. Water Resources Council 1978), which make up the contiguous 48 states of the US (Fig. [SI.1](#) and Table [SI.3](#) of Supplemental Material). The natural water flows and existing water diversions between ASRs result in three multi-ASR networks (of 69, 10, and four ASRs) and 15 single-ASR networks that drain to the ocean or into Mexico or Canada, or are closed basins (Fig. [SI.2](#) of Supplemental Material). We use the MODSIM hydrologic network model (Labadie and Larson 2007) to route water and simulate water management in each network. The simulations provide annual values of water flows between ASRs, reservoir storage and evaporation in each ASR, and water assigned to each demand, all of which depend both on climate and the following priorities: (1) in-stream flow requirements, (2) trans-ASR diversions, (3) water depletions, and (4) reservoir storage. These priorities recognize the importance of guaranteeing a sufficient amount of water for environmental and ecosystem needs (set as 10 % of the historical average streamflow, see [Supplemental Material](#)) before water is diverted for other uses, and allow trans-ASR diversions to occur before within-ASR diversions. With this set of priorities we ignore detailed basin-specific operating rules that could condition some trans-ASR diversions, perhaps allowing some within-ASR demands to be met before the trans-ASR diversion is fully satisfied. For example, our priorities satisfy the full diversion from the Sacramento Basin to southern California via the State Water Project before local diversions in the Sacramento Basin are met. Because storage is assigned the lowest priority, water is stored only after all reachable demands are satisfied.

For each of the six alternative GCM/SRES climate projections examined, the first and second order moments of the probability distribution functions of S , D , and Z and of their corresponding hydro-climatic drivers are estimated from the output of the hydrologic network model simulations over the period 1953 to 2090. We assess current vulnerability over the period 1986–2005 and future vulnerability over the four 20-year periods centered at 2020, 2040, 2060 and 2080.

4 Current vulnerability

The water supply system for much of the larger Southwest of the US plus parts of California, southern Oregon, the central Great Plains, and parts of the eastern plains of Colorado and southern Wyoming, is vulnerable under current hydro-climatic and socio-economic conditions (Fig. 1a). However, only a few areas show vulnerability values exceeding 0.023 (i.e., areas with reliability ratios less than 2 for Gaussian distributed surplus, Fig. SI.3a) at the ASR scale, and they tend to be those that rely heavily on mining of groundwater.

5 Sensitivity of vulnerability to climate change

Understanding how a water supply system responds to changes in climatic and socio-economic conditions is essential for future water management planning. Future changes in vulnerability depend both on the sensitivity of vulnerability to unit changes in the mean and standard deviation of S and D (i.e., $\partial V/\partial \mu_S$, $\partial V/\partial \sigma_S$) and on the actual changes in mean and standard deviation of S and D (i.e., $d\mu_S$, $d\sigma_S$) (see Eq. A.4 of Appendix A). The sensitivity of vulnerability is the local gradient of the multi-dimensional vulnerability surface and represents the change in vulnerability resulting from a unit change in the independent variables (i.e., first and

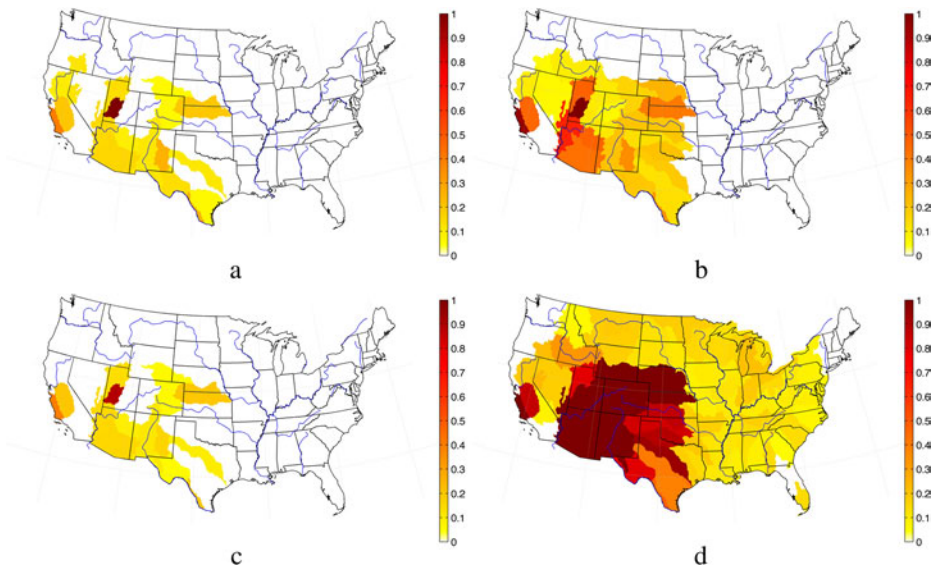


Fig. 1 a. Current vulnerability. b. Vulnerability in 2060 projected by the CGCM model under the A1B SRES scenario. c. Composite map of minimum vulnerability and d. composite map of maximum vulnerability for 2060 from projections by six GCM/SRES combinations

second order moments of S and D). With respect to the means, vulnerability decreases as mean supply (and P) increases (Eq. A.7), and increases as mean demand (and E) increases (Eq. A.8).

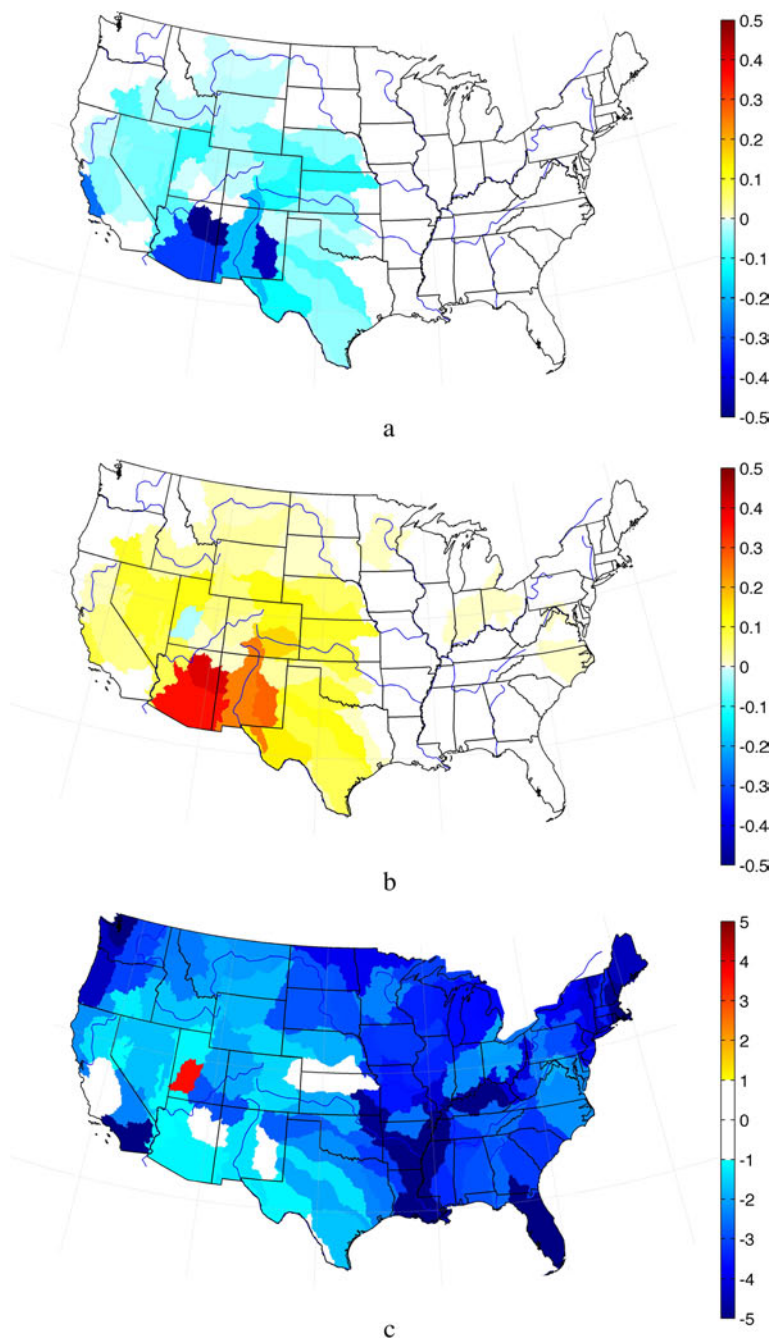


Fig. 2 Current sensitivity of vulnerability to changes in: **a.** mean water supply, $\partial V / \partial \mu_S$ [cm^{-1}]; and **b.** standard deviation of water supply, $\partial V / \partial \sigma_S$ [cm^{-1}]. **c.** Ratio of $\partial V / \partial \sigma_S$ to $\partial V / \partial \mu_S$

Figures 2a and SI.4a show that, currently, the magnitude of this sensitivity tends to be larger in those areas of the western US exhibiting reliability ratios less than two (Fig. SI.3a). These areas, in addition to being vulnerable under the current conditions, are therefore more prone to large changes in vulnerability than other areas for the same change in P , E , S , or D . In other words, these areas are vulnerable because their mean surplus is small compared to the standard deviation of surplus under the current conditions, and because they are more sensitive to unit changes in the mean and variance of surplus.

How changes in the standard deviations of S and D impact vulnerability depends on the value of the mean surplus (see Eqs. A.9 and A.10). Where the mean surplus is positive, as it is over much of the US, as the standard deviations of S and D (and P and E) increase so does the vulnerability of water supply (Fig. 2b; also see Fig. SI.4b in Supplemental Material). Conversely, where mean surplus is negative, increases in the standard deviations of S or D (also P or E) lead to decreases in vulnerability, (i.e., $\partial V/\partial\sigma_S < 0$ and $\partial V/\partial\sigma_D < 0$). Currently, negative mean surplus occurs only in the Sevier Lake basin in Utah, but in the future this condition is projected to occur under all GCM/scenario combinations in most of the arid Southwest. Under the CGCM/A2 projections, for example, a negative mean surplus, and thus a negative sensitivity, is projected to occur in central and coastal California, Utah, the middle and lower Colorado River, the South and North Platte basins, Arizona, Nebraska and Kansas (Foti 2011).

Except for only five ASRs (namely, 1010-Kansas, 1304-Upper Pecos, 1501-Little Colorado, 1803-San Joaquin Tulare, and 1805-Central California Coastal, Fig. SI.1), vulnerability of water supply is currently more sensitive to changes in the standard deviation of supply than to changes in the mean of supply (Fig. 2c). The opposite is true with respect to demand such that for nearly all ASRs (except 304-St. Johns Suwannee, 305-Southern Florida, 1602-Sevier Lake, and 1806-Southern California Coastal) vulnerability is more sensitive to changes in the mean of demand than to changes in the standard deviation of demand (Fig. SI.4c of Supplemental Material). Because water supply is mainly a function of P and E , these results underscore the importance of improving our ability to project changes in the variance of climatic drivers of hydrologic response (e.g., precipitation and potential evapotranspiration).

6 Projected changes in climate variables and demand

Under the CGCM/A1B climate projections, increases in mean precipitation and mean evapotranspiration from the current period to 2060 are projected for most of the US except in parts of the Southwest, Texas, Oregon, and California (Foti 2011; Foti et al. 2012). Because the increases in evaporation tend to exceed the increases in precipitation, mean yield is projected to decrease for most of the US, except in parts of the Southwest and Texas where it is projected to increase slightly (Foti 2011; Foti et al. 2012). As a result, mean supply is projected to decrease for most of the US, except in isolated basins of the Southwest and the southern Plains where it is projected to increase slightly (Fig. 3a). Mean water demand is projected to increase generally over the entire US, but especially in the lower Mississippi river basin largely as a result of growth in irrigated agriculture (Fig. 3b). The standard deviation of supply is projected to decrease for most of the US, except for a few scattered basins in the southwest and the northeast where it is projected to increase. Large decreases are projected for the northwest and for the eastern half of the country (Fig. 3c). It should be noted that decreases in the standard deviation of water supply do not necessarily stem from decreases in the standard deviation of water yield. In fact, a primary function of a

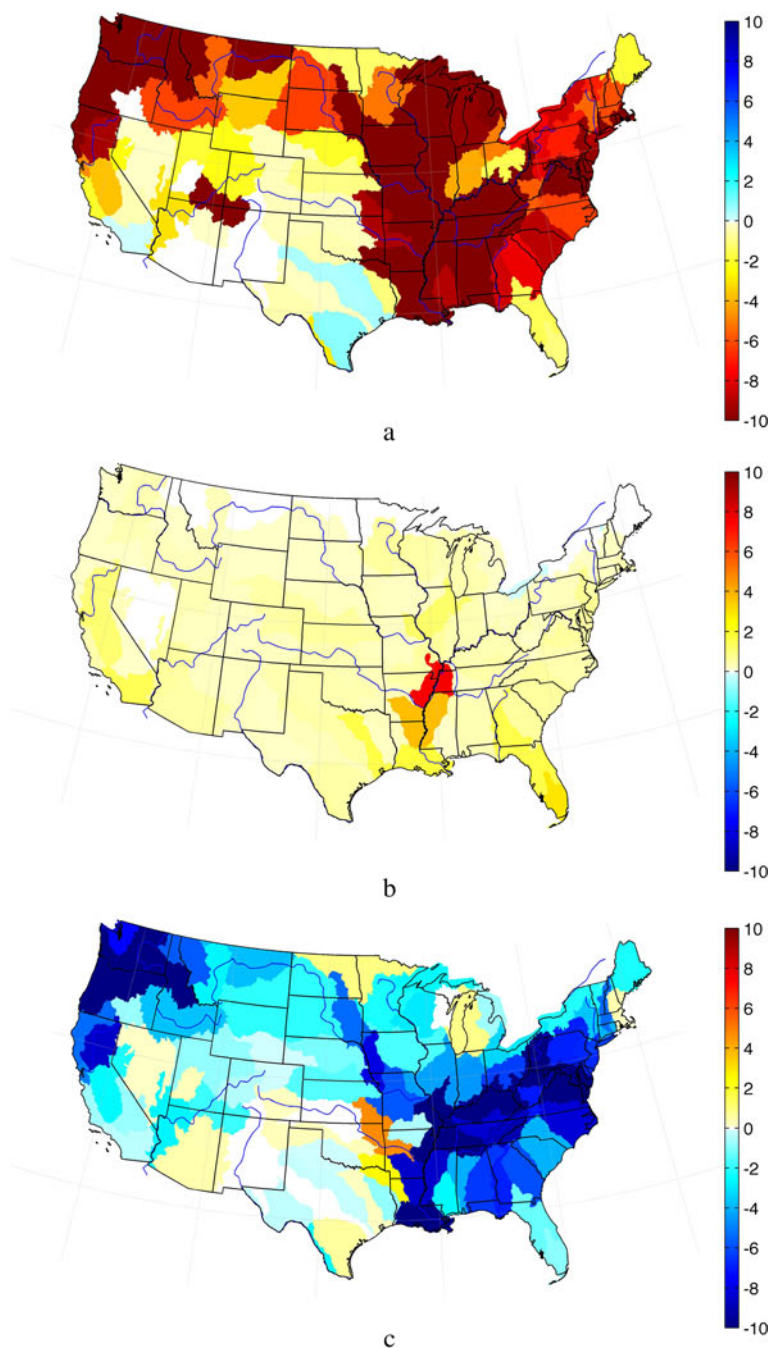


Fig. 3 Change from the current period to 2060, as projected by the CGCM model under the A1B scenario, in: **a.** mean supply [cm]; **b.** mean demand [cm]; **c.** standard deviation of supply [cm]

managed water supply system is precisely to reduce the variance in the hydrologic yield through the combined effect of water diversions and storages. Finally, the standard

deviation of demand is projected to decrease slightly in California, coastal Oregon and Washington; and to increase slightly in the central and southern Plains (Fig. SI.5).

7 Future vulnerability

Under the CGCM/A1B climate projections, the southwestern US and parts of California, the Great Basin, and the Great Plains are the areas projected to face the greatest levels of vulnerability (Fig. 1b and SI.3b). Dramatic increases in vulnerability are projected for the lower Colorado River Basin, the central Great Plains, central California, and parts of the Great Basin. Large increases are also expected in the Rio Grande basin and Texas.

Vulnerability is projected to change as a result of changes in the probability distribution functions of supply and demand (i.e., changes in μ_S , σ_S , μ_D , and σ_D). Changes in mean D from the current period to 2060 are projected to induce increases in vulnerability in the Southwest, central California, and the southern Great Plains, and to have essentially no effect on vulnerability over the rest of the country (Fig. SI.6a). Changes in the standard deviation of D are projected to have negligible effects on vulnerability except in central California and the Little Colorado basin where they will induce decreases of vulnerability, and parts of the central and southern Great Plains, where they will induce increases of vulnerability (Fig. SI.6b). Projected changes in the mean of S lead to increases in vulnerability for most of the western US as well as parts of Tennessee, Alabama, Georgia, Ohio, Indiana, the Carolinas and Virginia, with large increases for the lower Colorado River basin and central and coastal California (Fig. 4a). However, projected changes in the standard deviation of S lead to decreases of vulnerability in the same areas (Fig. 4b). For most of the US, the largest contributions to changes in vulnerability come from changes in S . However, for some areas of the West changes in vulnerability are caused mainly by changes in D (Fig. 4c).

Changes in both mean P and mean E contribute to increasing vulnerability in the larger Southwest. However, as shown in Fig. 5a, vulnerability changes from P are larger than those from E . The opposite is true for the rest of the country where changes in vulnerability from E are larger than those from P (Fig. 5a). Finally, changes in vulnerability resulting from projected changes in the standard deviation of surplus are of about the same magnitude or larger than those from changes in the corresponding mean for the area west of the Rockies and the area east of the Mississippi river; over the rest of the US, the opposite is true generally (Fig. 5b).

8 Effect of groundwater mining

Because comprehensive data were lacking, groundwater mining was not included in water supply in the above results. However, data are available for some areas, including the Central Valley aquifer in California (e.g., Famiglietti et al. 2011), and the Ogallala aquifer in the US High Plains (e.g., Scanlon et al. 2012). We find that the impact of groundwater mining on vulnerability in these areas is significant. The reduction of current vulnerability is 100 % for ASR 54-North South Platte basins, which relies in part on the Ogallala aquifer, and 62.8 % for ASR 94-San Joaquin Tulare basins, which relies in part on the Central Valley aquifer (see Fig. 6a). If groundwater mining rates were to remain at their current levels, those reductions would be 20 % and 57 % in 2060, respectively (see Fig. 6b.) Therefore, because of the combined effects of projected increases in demand and reductions in yield, groundwater mining rates would need to continue increasing in order for vulnerability to be maintained at current levels. Such increases may be unsustainable.

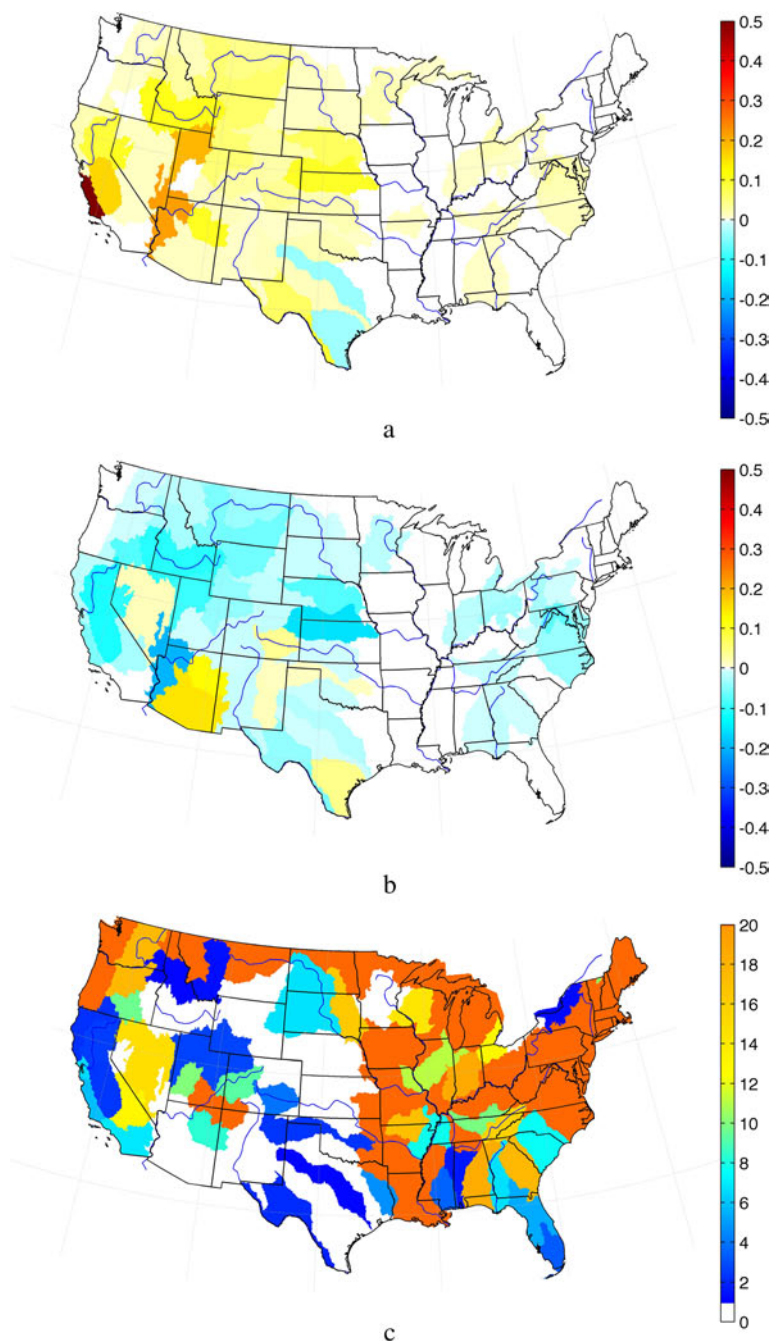


Fig. 4 Changes in vulnerability from the current period to 2060, as projected by the CGCM model under the A1B scenario, resulting from changes in: **a.** the mean of supply; **b.** the standard deviation of supply. **c.** Relative importance of changes in vulnerability resulting from changes in supply with respect to those resulting from changes in demand, $\Delta V(\Delta S)/\Delta V(\Delta D)$

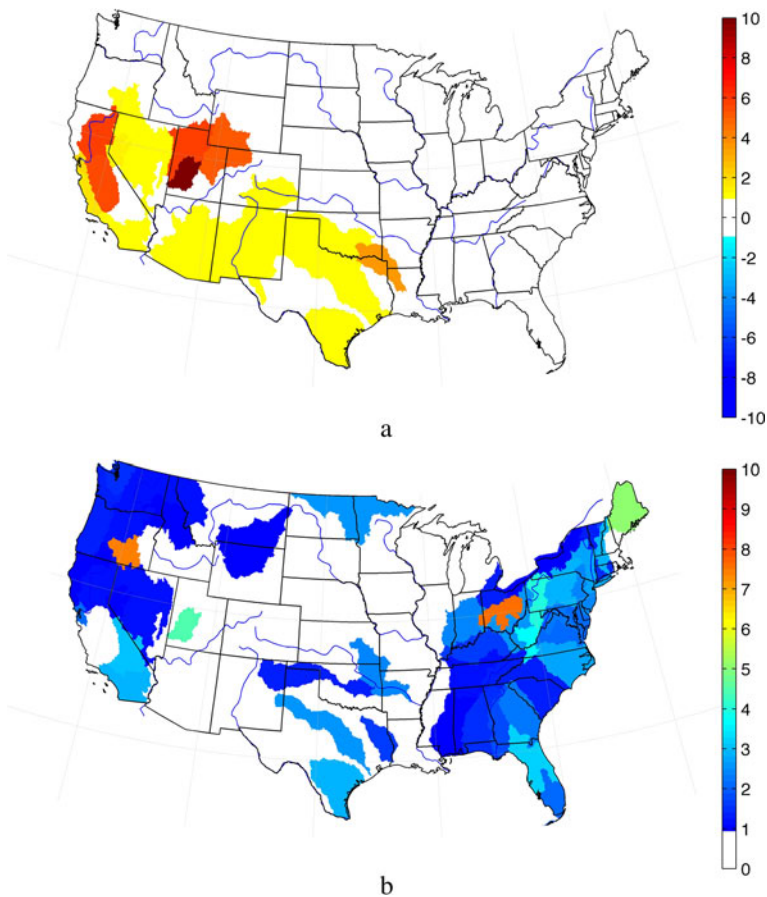


Fig. 5 Relative importance of factors affecting change in vulnerability from the current period to 2060 as projected by the CGCM model under the A1B scenario: **a.** ratio of the change in vulnerability due to change in the mean of precipitation to the change in vulnerability due to change in the mean of evapotranspiration, $\Delta V(\Delta\mu_p)/\Delta V(\Delta\mu_E)$. **b.** ratio of the change in vulnerability due to change in the standard deviation of surplus to the change in vulnerability due to change in the mean of surplus, $\Delta V(\Delta\sigma_z)/\Delta V(\Delta\mu_z)$

9 Uncertainty about the projections

Providing estimates for more than one socio-economic scenario, each simulated using a set of GCMs, is one way to capture uncertainty in the projections of vulnerability. Composite maps of the maximum (Fig. 1c), minimum (Fig. 1d), and range of values of vulnerability (Fig. SI.7) from among the projections by the MIROC, CSIRO, and CGCM models under scenarios A1B and A2 show that although there is general agreement that the water supply system of the southwestern US is the most vulnerable to hydro-climatic variability and socio-economic changes, there is also a great deal of disagreement about the degree of change in vulnerability. The disagreement is greatest in the central and southern Great Plains, the Rio Grande basin, the lower Colorado River basin, the San Joaquin river basin in California, and southern Idaho (see Foti 2011; Foti et al. 2012 and Figs. SI.8–SI.12 for additional graphical representation of the uncertainty in these projections and of the differences among the scenario/model combinations).

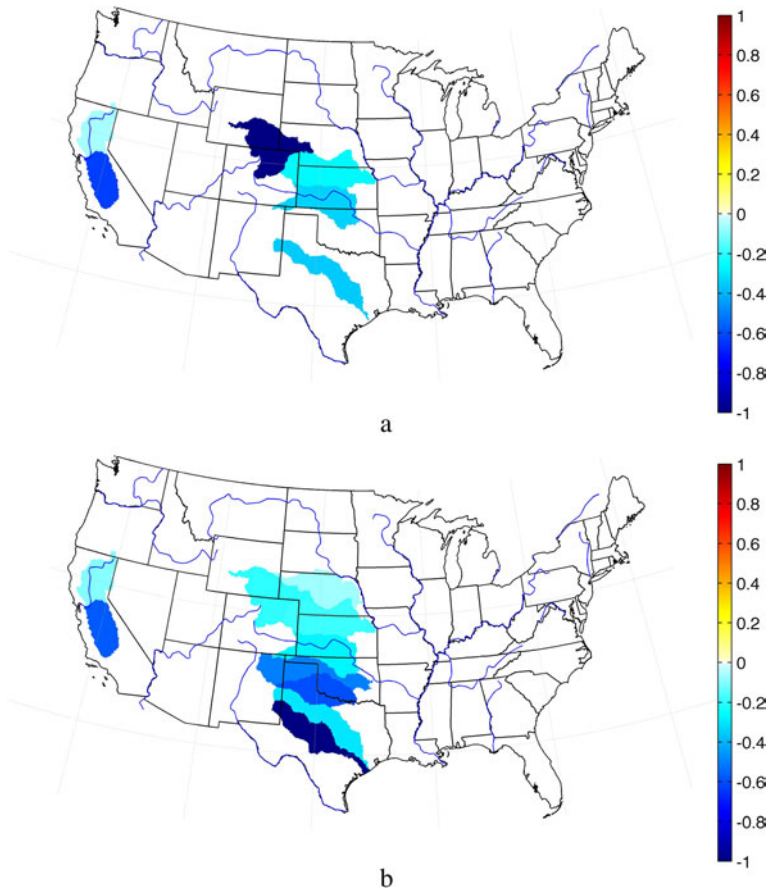


Fig. 6 Fractional reduction of vulnerability resulting from groundwater mining of the Ogallala aquifer and the Central Valley, California aquifer. **a)** Reduction of current vulnerability; **b)** Reduction of vulnerability in 2060

10 Concluding remarks

These results assume no modifications to the physical structure of US water networks. In addition, in-stream flow requirements and trans-ASR diversions were set constant, thereby ignoring possible future changes in surface water redistribution. Indeed, a primary purpose of this assessment is to point to those locations where adaptation will be most needed. Options for reducing vulnerability include, in addition to continued groundwater mining, increases in storage capacity, enlarged trans-basin diversion capacity, enhanced water conservation efforts, and reductions in demand drivers (e.g., in irrigated area).

Our simulations at the ASR scale show that across the 48 western ASRs that have any storage capacity in these simulations, only in five ASRs is a shortage condition followed by storage capacity being completely replenished at some time during the simulations. Therefore, these five ASRs (namely, 1008-Niobrara Platte Loup, 1010-Kansas, 1103-Arkansas Cimarron, 1106-Red Washita, and 1304-Upper Pecos) are potential candidates for additional storage. Among the other 43 western ASRs, either shortage never occurs (this is the case in 35 ASRs) or storage volumes never reach full capacity after falling to

zero (this occurs in the remaining eight ASRs, located in Water Resource Regions 10, 11, 14, 15, 16, and 18). Thus, at the annual time scale, water scarcity in those eight ASRs is primarily due to demand–supply imbalance rather than to insufficient storage capacity. Along the Colorado River, for example, storage volumes in Lakes Powell and Mead are projected to drop to zero and never fully recover, a finding supported by other regional studies (Barnett and Pierce 2008). Thus, increases in storage capacity are not a successful adaptation strategy in these most vulnerable regions (Christensen and Lettenmaier 2007). On the other hand, in the eastern ASRs, annual storage volumes seldom drop below capacity and never reach zero. Of course, these results apply only to annual aggregate ASR storage, and do not preclude the possibility of useful additions to storage in selected upstream locations to reduce intra-annual (e.g., seasonal) and/or sub-ASR (e.g., county level) vulnerability.

Importantly, this analysis is carried out on an annual basis. However, it is clear that quantification of the intra-annual variability of vulnerability (driven by intra-annual variability of the climatic and hydro-economic drivers) is important. Because intra-annual changes in climatic and hydro-economic drivers may crucially impact the seasonal patterns of water supply (Barnett et al. 2005; Clow 2009; Dettinger et al. 2004; Hamlet et al. 2005) and thus vulnerability, the examination of seasonal and finer spatial scale vulnerability is essential. Such examination is the subject of current research by the authors.

Contrary to a prior global scale conclusion (Vörösmarty et al. 2000) and in concert with a recent US study (Roy et al. 2012), we find that future increases in the vulnerability of water supply in many ASRs will depend more on changes in water yield than on growth in water demand. Total water use in the US has leveled off in recent years (Kenny et al. 2009) as irrigated area in the West has diminished and the efficiency of water withdrawals in nearly all sectors has improved (Brown 2000; Brown et al. 2013). Although projected climate change will increase water demand, future water use efficiency improvements will largely mitigate that impact so that overall increases in desired water use are expected in many ASRs to be modest in comparison with the effect of climatic changes on water yield and thus on water supply. Our result that changes in the variability (i.e., standard deviation) of the hydro-climatic drivers are as important, or more, than changes in the corresponding means emphasizes the need for renewed efforts to improve our GCMs and to incorporate higher-order moments in our analyses.

Our finding of greater vulnerability and declining storage levels in the Southwest and central and southern Great Plains of the US is in agreement with other regional-scale (Barnett et al. 2004; Barnett and Pierce 2008; Barnett and Pierce 2009; Cayan et al. 2010; Christensen et al. 2004; Dawadi and Ahmad 2012) and large-scale assessments (Hurd et al. 1999; Roy et al. 2012; Vörösmarty et al. 2000). However, our analysis is the only one that approaches vulnerability from a probabilistic perspective and that explicitly includes the effects of reservoir storage and water routing among basins (via both natural routes and artificial trans-basin diversions). In addition, our work is based on a more comprehensive effort to project water demand, and where data are available we also estimate the impact of groundwater mining on water supply vulnerability. The probabilistic methodology we use can be applied to any vulnerability analysis, and is the only methodology that both accounts for the probabilistic character of the drivers and allows for explicit inclusion of thresholds.

Acknowledgments This study was performed in response to the Forest and Rangeland Renewable Resources Planning Act of 1974 (public law 93–378). Funding was provided by the U.S. Forest Service with substantial contributions from Colorado State University. Partial funding was provided by the U.S. Bureau of Reclamation.

Appendix A - vulnerability analysis

In general, vulnerability of water supply to shortage may be defined as the probability that the supply is less than the demand; that is,

$$V = \Pr[S < D] = \Pr[S - D < 0] \quad (\text{A.1})$$

where S is water supply, and D is water demand. Also, in general,

$$S = P - E + I + Q_{div} + SV \quad (\text{A.2})$$

where P is precipitation, E is actual evapotranspiration, I is the net input from upstream, Q_{div} is the net diversions (difference between diversions into and diversions out of the system), and SV is reservoir and other storage.

Defining the surplus, Z , as the difference between supply and demand, Eq. (A.1) can be rewritten as,

$$V = \Pr[Z < 0] = \Pr\left[\frac{Z - \mu_Z}{\sigma_Z} < -\frac{\mu_Z}{\sigma_Z} = -\beta\right] \quad (\text{A.3})$$

where $\mu_Z = \mu_S - \mu_D$, $\sigma_Z^2 = \sigma_S^2 + \sigma_D^2 - 2\text{cov}(S, D)$, $\beta = \mu_Z / \sigma_Z$, and μ_S , μ_D , σ_S , and σ_D , $\text{cov}(S, D)$, are the mean, standard deviation and covariance of water supply and water demand.

Therefore, as is clear from Eq. (A.3), the vulnerability of water supply as defined in Eq. (A.1) is a function of the mean, standard deviation and covariance of supply and water demand, that is, μ_S , μ_D , σ_S , and σ_D , $\text{cov}(S, D)$.

We may then express the total change in vulnerability, dV , as a function of the individual contributions of changes in μ_S , μ_D , σ_S , and σ_D , $\text{cov}(S, D)$, as follows,

$$dV = \frac{\partial V}{\partial \mu_S} d\mu_S + \frac{\partial V}{\partial \mu_D} d\mu_D + \frac{\partial V}{\partial \sigma_S} d\sigma_S + \frac{\partial V}{\partial \sigma_D} d\sigma_D + \frac{\partial V}{\partial \text{cov}(S, D)} d\text{cov}(S, D) \quad (\text{A.4})$$

where each of the partial derivatives represents the sensitivity of the vulnerability to unit changes in each of the independent variables μ_S , μ_D , σ_S , and σ_D , $\text{cov}(S, D)$. In addition, each of the five terms of Eq. (A.4) represents the contribution to the total change in vulnerability resulting from the changes in μ_S , μ_D , σ_S , and σ_D , $\text{cov}(S, D)$.

For the case of normally distributed surplus, Eq. (A.1) can be rewritten as,

$$V = \Pr[Z < 0] = \Pr\left[\frac{Z - \mu_Z}{\sigma_Z} < -\frac{\mu_Z}{\sigma_Z} = -\beta\right] = [2\pi\sigma_Z^2]^{-0.5} \int_{-\infty}^0 e^{-\frac{(z - \mu_Z)^2}{2\sigma_Z^2}} dz \quad (\text{A.5})$$

In the case of non-Gaussian Z , Eq. (A.5) corresponds to a First Order Second Moment approximation.

Carrying out the integral of Eq. (A.5) yields,

$$V(\mu_S, \mu_D, \sigma_Z) = \frac{1}{2} + \frac{1}{2} \text{erf}\left[\frac{(-\mu_S + \mu_D)}{\sqrt{2}\sigma_Z}\right] \quad (\text{A.6})$$

where $\text{erf}()$ is the Gauss error function (also known as the probability integral).

The partial derivatives appearing in Eq. (A.4) are obtained by differentiating Eq. (A.6) with respect to μ_S , μ_D , σ_S , and σ_D , $\text{cov}(S, D)$. The resulting derivatives are shown in Eqs. (A.7–A.11).

$$\frac{\partial V}{\partial \mu_S} = -[2\pi(\sigma_Z^2)]^{-0.5} e^{-\frac{(-\mu_S + \mu_D)^2}{2\sigma_Z^2}} \quad (\text{A.7})$$

$$\frac{\partial V}{\partial \mu_D} = [2\pi(\sigma_Z^2)]^{-0.5} e^{-\frac{(-\mu_S + \mu_D)^2}{2\sigma_Z^2}} \quad (\text{A.8})$$

$$\frac{\partial V}{\partial \sigma_S} = -\sigma_S(-\mu_S + \mu_D) [2\pi(\sigma_Z^2)^3]^{-0.5} e^{-\frac{(-\mu_S + \mu_D)^2}{2\sigma_Z^2}} \quad (\text{A.9})$$

$$\frac{\partial V}{\partial \sigma_D} = -\sigma_D(-\mu_S + \mu_D) [2\pi(\sigma_Z^2)^3]^{-0.5} e^{-\frac{(-\mu_S + \mu_D)^2}{2\sigma_Z^2}} \quad (\text{A.10})$$

$$\frac{\partial V}{\partial \text{cov}(S, D)} = (-\mu_S + \mu_D) [2\pi(\sigma_Z^2)^3]^{-0.5} e^{-\frac{(-\mu_S + \mu_D)^2}{2\sigma_Z^2}} \quad (\text{A.11})$$

Although not included here for brevity, the above analysis can be easily extended to define changes in vulnerability as a function of changes in the probabilistic characteristics of P , and E , explicitly.

References

- Barnett TP, Pierce DW (2008) When will Lake Mead go dry? *Water Resour Res* 44, W03201
- Barnett TP, Pierce DW (2009) Sustainable water deliveries from the Colorado River in a changing climate. *Proc Natl Acad Sci* 106:7334–7338
- Barnett T, Malone R, Pennell W, Stammer D, Semtner B, Washington W (2004) The effects of climate change on water resources in the West: introduction and overview. *Clim Chang* 62:1–11
- Barnett TP, Adam JC, Lettenmaier DP (2005) Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature* 438:303–309
- Brown TC (2000) Projecting U.S. freshwater withdrawals. *Water Resour Res* 36:769–780
- Brown TC, Foti R, Ramirez JA (2013) Projected freshwater withdrawals in the United States under a changing climate. *Water Resour Res* 49:1259–1276
- Cayan DR, Das T, Pierce DW, Barnett TP, Tyree M, Gershunov A (2010) Future dryness in the southwest US and the hydrology of the early 21st century drought. *Proc Natl Acad Sci* 107(50):21271–21276
- Christensen NS, Lettenmaier DP (2007) A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River Basin. *Hydrol Earth Syst Sci* 11:1417–1434
- Christensen N, Wood A, Voisin N, Lettenmaier D, Palmer R (2004) The effects of climate change on the hydrology and water resources of the Colorado River Basin. *Clim Chang* 62:337–363
- Clow DW (2009) Changes in the timing of snowmelt and streamflow in Colorado: a response to recent warming. *J Clim* 23:2293–2306
- Dawadi S, Ahmad S (2012) Changing climatic conditions in the Colorado River Basin: implications for water resources management. *J Hydrol* 430–431:127–141
- Dettinger M, Cayan D, Meyer M, Jeton A (2004) Simulated hydrologic responses to climate variations and change in the Merced, Carson, and American River Basins, Sierra Nevada, California, 1900–2099. *Clim Chang* 62:283–317

- Eagleson PS (1978) Climate, soil, and vegetation. 6. Dynamics of annual water-balance. *Water Resour Res* 14: 749–764
- Famiglietti JS, Lo M, Ho SL, Bethune J, Anderson KJ, Syed TH, Swenson SC, Linage CR, Rodell M (2011) Satellites measure recent rates of groundwater depletion in California's Central Valley. *Geophys Res Lett* 38:L03403
- Foti R (2011) Part A: a probabilistic framework for assessing vulnerability to climate variability and change: the case of the US water supply system. Part B: dynamics of self-organized vegetation patterns. PhD thesis, Colorado State University, Fort Collins
- Foti R, Ramirez JA, Brown TC (2012) Vulnerability of U.S. water supply to shortage: a technical document supporting the Forest Service 2010 RPA Assessment. Gen. Tech. Rep. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, p 147
- Hamlet AF, Mote PW, Clark MP, Lettenmaier DP (2005) Effects of temperature and precipitation variability on snowpack trends in the Western United States*. *J Clim* 18:4545–4561
- Hurd B, Leary N, Jones R, Smith J (1999) Relative regional vulnerability of water resources to climate change. *J Am Water Res Assoc* 35:1399–1409
- Kenny JF, Barber NL, Hutson SS, Linsey KS, Lovelace JK, Maupin MA (2009) Estimated use of water in the United States in 2005. U. S. Geological Survey, Reston, p 52
- Kochendorfer JP, Ramirez JA (1996) Integrated hydrological/ecological/economic modeling for examining the vulnerability of water resources to climate change. In: North American Water and Environment Congress '96 – ASCE. ASCE, New York, pp. 2157–2162
- Labadie JW, Larson R (2007) MODSIM 8.1: River basin management decision support system: user manual and documentation. Colorado State University, Fort Collins, p 123
- Nakicenovic N, Alcamo J, Davis G, de Vries B, Fenham J, Gaffin S, Gregory K, Grubler A, Jung TY, Kram T, Rovere ELL, Michaelis L, Mori S, Morita T, Pepper W, Pitcher H, Price L, Riahi K, Roehrl A, Rogner H-H, Sankovski A, Schlesinger M, Shukla P, Smith S, Swart R, Sv R, Victor N, Dadi Z (2000) Emissions scenarios: a special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, p 599
- Price DT, McKenney DW, Papadopol P, Logan T, Hutchinson MF (2006) High-resolution climate change scenarios for North America. Canadian Forestry Service, Sault Ste, Marie
- Roy SB, Chen L, Girvetz E, Maurer EP, Mills WB, Grieb TM (2012) Projecting water withdrawal and supply for future decades in the U.S. under climate change scenarios. *Environ Sci Technol* 46:2545–2556
- Scanlon BR, Faunt CC, Longuevergne L, Reedy RC, Alley WM, McGuire VL, McMahon PB (2012) Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. *PNAS* 109:9320–9325
- U.S. Water Resources Council (1978) The nation's water resources 1975–2000. U. S. Government Printing Office, Washington
- Vörösmarty CJ, Green P, Salisbury J, Lammers RB (2000) Global water resources: vulnerability from climate and population growth. *Science* 289:284–288
- Zarnoch SJ, Cordell HK, Betz CJ, Langner L (2010) Projecting county-level populations under three climate change future scenarios: a technical document supporting the Forest Service 2010 RPA assessment. Southern Research Station, U. S. Forest Service, Ashville, p 8